Complex Systems at NASA – Help from Natural Systems

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Outline

- Systems Engineering Characteristics
- Systems Engineering Framework
- System Complexity
  - Nature provides the examples
  - Definition
  - Properties
  - Modeling Properties
- Model Selection Lessons Learned from Natural Systems
- Summary

System Engineering Research Consortium Focus

- System Engineering of Complex Systems is not well understood

- System Engineering of Complex Systems is Challenging
  - System Engineering can produce elegant solutions in some instances
  - System Engineering can produce embarrassing failures in some instances
  - Within NASA, System Engineering is frequently unable to maintain complex system designs within budget, schedule, and performance constraints

- "How do we Fix System Engineering?"
  - Michael D. Griffin, 61st International Astronautical Congress, Prague, Czech Republic, September 27-October 1, 2010
  - Successful practice in System Engineering is frequently based on the ability of the lead system engineer, rather than on the approach of system engineering in general
  - The rules and properties that govern complex systems are not well defined in order to define system elegance

- 4 characteristics of system elegance proposed as:
  - System Effectiveness
  - System Efficiency
  - System Robustness
  - Minimizing Unintended Consequences

Approach

- Define basis of System Engineering as an Engineering Discipline

- Three (3) thrusts to accomplish this
  - System Works
    - Understanding objectively what works in current system development (SLS)
      - Follow SLS through DCR to study full development phase (once in 40 year opportunity)
    - Distill the laws governing system engineering in complex systems by studying this approach through a combination of academic research with practicing system engineers
      - Document the laws governing complex system interactions identified in the research
      - Capture practical guidance from the research in a System Engineering Practitioner's Guide

  - System Design
    - Apply the laws of governing Complex Systems in an elegant manner in the next major complex system development (Mars Transportation System)
      - Apply and refine guidance in System Engineering Practitioner's Guide

  - System Academy
    - Train new and practicing system engineers in the engineering basis of the discipline
      - Preliminary Academic Curriculum
      - Current work force training courses

Consortium

- Research Process
  - Multi-disciplinary research group that spans systems engineering areas
  - Selected researchers who are product rather than process focused

- List of Consortium Members
  - UAH – Phil Farrington, Paul Collopy, Dawn Utley, Laird Burns, Wes Colley, Bryan Mesmer, Bob Ryan, & Joey Shelton
    - System Cost Modeling – Paul Collopy
    - System Exergy – PJ Benefield, Bryan Mesmer, Joey Shelton
    - System Complexity, Chief Engineer Interviews – Laird Burns
    - Program/Engineering Decision Making – Dawn Utley
  - UCCS– Disciplinary Formalization of System Engineering - Stephen Johnson
  - Texas A&M – Designing Robust Engineered Systems - Richard Malak
  - MIT – Informal representation and team decision-making in Complex Engineering Systems - Maria Yang
  - Iowa State – SE Processes Evaluation - Paul Componation
  - University of Dayton – System Exergy – John Doty
  - Missouri University of Science and Technology - System Exergy – Dave Riggins
  - GWU Space Policy Institute – Application of Policy and Law – Zoe Szajnfarber
  - Schafer Corporation – Mike Griffin

- Previous Consortium Members
  - Stevens Institute of Technology – Dinesh Verma
  - Spaceworks – John Olds (Cost Modeling Statistics)
  - Alabama A&M – Emeka Dunu (Supply Chain Management)
  - George Mason – John Gero (Agent Based Modeling)
  - Oregon State – Irem Tumer (Electrical Power Grid Robustness)
  - Arkansas – David Jensen (Failure Categorization)

20 graduate students and 3 undergraduate students supported to date

System Engineering Framework Mapping

Research Framework

Systems Engineering Focus Areas						
Understanding Mission	**Physics Relationships**			**Organization Structure & Relationships**	**Regulatory Requirements**	
	Performance	Cost/Schedule	Product Risk	Organization		**Product Attributes**
Chief Engineer Interviews (Burns/UAH) Program/Engineering Decision Making (Utley/UAH) SE Processes Evaluation (Componation/ISU)	**Interdisciplinary Design Model (Johnson/UCCS)** **System Entropy and Information Entropy (Doty/UD, Benefield/UAH, Colley/UAH)** SE Processes Evaluation (Componation/ISU)	**Physics Based Cost Model (Collopy/UAH)** **SE Processes Evaluation (Componation/ISU)** **Chief Engineer Interviews (Burns/UAH)**	SE Processes Evaluation (Componation/ISU)	**SE Processes Evaluation (Componation/ISU)** **Program/Engineering Decision Making (Utley/UAH)** **Informal representation and team decision-making in complex engineering systems (Yang/MIT)** **Chief Engineer Interviews (Burns/UAH)**	**Policy and Law Implications to System Engineering (GWU/Szajnfarber)**	**System Effectiveness**
Design Robust Engineered Systems (Malak/Texas A&M)	**Interdisciplinary Design Model with Robustness Measure (Johnson/UCCS, Malak Texas A&M)**	**Physics Based Cost Model (Collopy/UAH)**		Physics Based Cost Model (Collopy/UAH)		**Robustness**
	System Entropy and Information Entropy (Doty/UD, Benefield/UAH, Colley/UAH)	**Physics Based Cost Model (Collopy/UAH)**		Physics Based Cost Model (Collopy/UAH)	**Policy and Law Implications to System Engineering (GWU/Szajnfarber)**	**Efficiency**
Social Model (MSFC/Watson)	**Failure Event Classification (MSFC/Watson, UCCS Johnson)**	Physics Based Cost Model (Collopy/UAH)	Social Model (MSFC/Watson) Failure Event Classification (MSFC/Watson, UCCS Johnson)	**Social Model (MSFC/Watson)**		**Unintended Consequence**

***Chief Engineering Interviews (Burns/UAH) - Applies to all cells in matrix**

Bold - Primary Research Area

- Primary Relationship (SE Focus Area x Product Attributes)
- Secondary Relationship (SE Focus Area x Product Attributes)
- Research Gaps at end of Exploration Phase

System Complexity: Natural or Engineered?

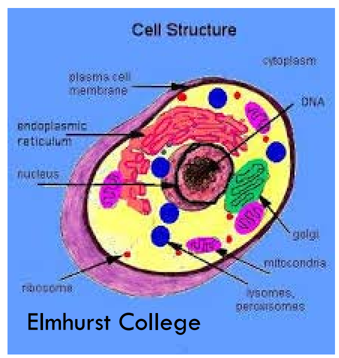
Space Launch System (SLS)

- Complex systems are the result of human engineering efforts
  - Space Launch System
  - Electrical Power Plants
  - Ships

Ikata Nuclear Power Plant, Japan, Wikipedia

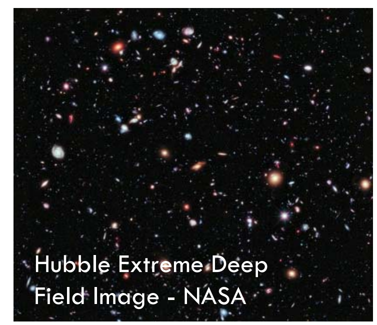
USS Enterprise, Wikipedia

- Complex systems/Complex Adaptive Systems naturally occur in nature
  - Cell Structure
  - Ecosystems
  - Meteorology
  - Cosmology



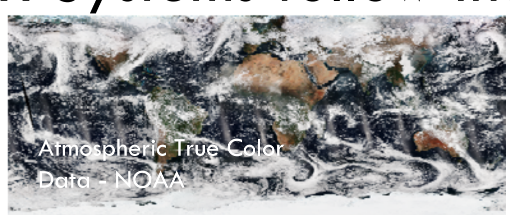
Elmhurst College

Bromeliad Wikipedia



Hubble Extreme Deep Field Image - NASA

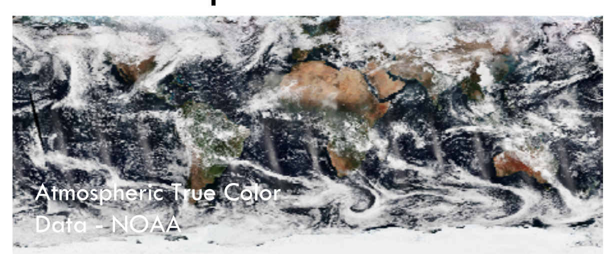
- Do these Complex Systems follow the same relationship rules?



Atmospheric True Color Data - NOAA

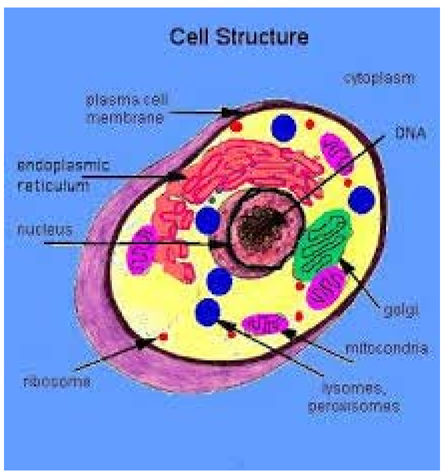
System Complexity: Natural or Engineered or Both?

- Do these Complex Systems follow the same relationship rules?
  - This is a question still to be answered.
- Complex Systems/Complex Adaptive Systems originate from human engineering and naturally
  - Systems Engineers seek to produce a system for some benefit to society and culture (exploration, trade, defense)
    - These are becoming more complex systems and complex adaptive systems
    - Complex systems/complex adaptive systems are engineered by natural complex systems (organizations)
  - Natural systems provide a learning ground for understanding complex systems and complex adaptive systems
    - These natural systems are believed to have the same basic properties of complexity that human engineered systems seek to attain
    - This is a point that needs further definition and mathematical proof



System Complexity Definition

- Complexity: A measure of a system's intricacy and comprehensibleness in interactions within itself and with its environment.



System Complexity Properties

- Properties:
  - Complex systems have a propensity to exhibit unexpected performance of intended function
  - Complex systems are aggregations of less complex systems
  - Complex systems exhibit properties not present in the individual subsystems but present in the integration of subsystems (emergent property)
  - Complex system interactions form networks within the system and with the system environments
    - Complex system interactions can be understood through control theory
  - Complex systems exhibit nonlinear responses to system stimuli
    - Complex systems are difficult to predict
  - Complex systems have local optimums
    - (Organizational Efficiency Determines ability to achieve local optimum)
  - Complex systems can be analyzed using two concepts:
    - laws (rules of interaction)
    - states (current state and prior history)

Systems Engineering Complexity

- Complex System Properties:
  - In general, it may be possible to optimize some CS for known design requirements but not for complex adaptive systems (CAS) (Holland, 2012).
  - Predictions of CS and CAS are challenging (Simon, 1996)
  - System engineering teams are organic systems with biological properties
  - Perpetual novelty is a characteristic of most CAS (Holland, 2014)
  - Recurring patterns are characteristics of CS (Holland, 2014)
  - CS can be analyzed using two concepts: laws (rules of interaction) and states (current state and prior history) (Holland, 2014)

*Compiled by UAH/Laird Burns

System Engineering Complexity Modeling Properties

- All Engineered Systems are designed, built, and operated to achieve goals.
  - Goals are expressions of intent of the designers, builder, and operators.
  - The intentions, and hence the goals of system designers, builders, and operators can and often do differ. They may or may not be compatible, and may or may not be explicitly documented.
- Expectations of system behavior are based on models. Models can be formal or informal.
- Formal modeling of system behaviors using mathematics, physical, and logic is less mistake-prone than methods that do not use formal models. This is primarily because formal models either reject invalid inputs, or if invalid inputs are accepted, can be searched for mistakes, or yield outputs that can be assessed for validity.
- Functions are defined as mappings of input states of state variables to output states of state variables, $y = f(x)$.
  - If the input states map to identical output states of a hypothesized function, there is no function.
  - Goals are expressed as constraints on the ranges of output state variables of a function. Goal = $rl < y < rh$, where $y = f(x)$.
  - Failure is defined as the unacceptable control of an output state variable of a function. Failure = $rl > y$, or $y > rh$, where $y = f(x)$.
- Requirements are formal written statements of goals.

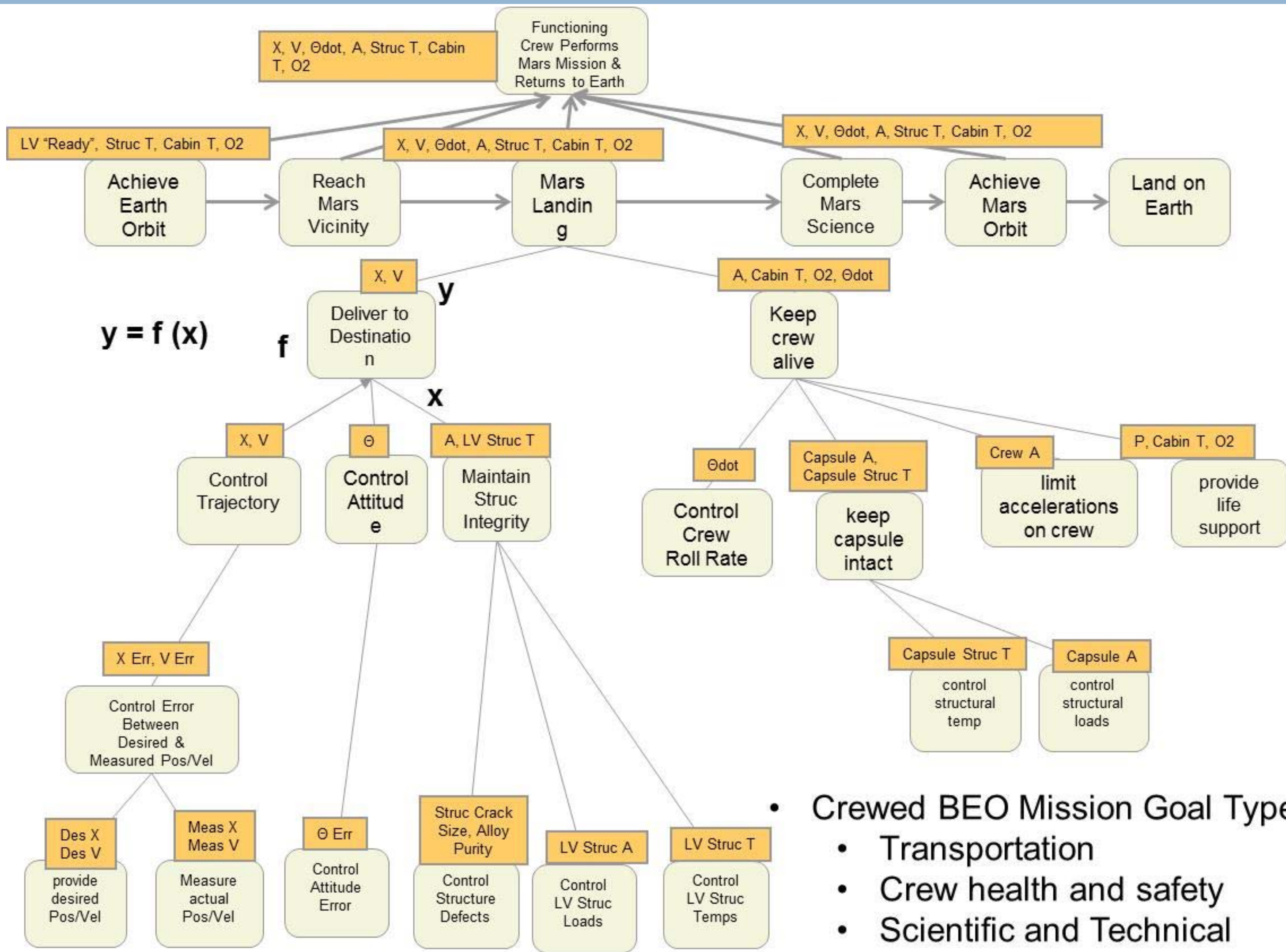
*Developed by UCCS/Stephen Johnson

System Engineering Complexity Modeling Properties

- System goals can be represented hierarchically, due to the hierarchical nature of intentions. Some goals define the ultimate intentions for the system, and other goals exist only to support them.
  - Since goals can be modeled hierarchically, and since goals are expressed as constraints on the ranges of output state variables of a function, functions can be modeled hierarchically as well.
- A system design implements the means by which functions operate and goals are achieved.
  - System design models are not hierarchical.
  - State variables are the primary connection between functional and design representations of the system, as they exist in both representation types.
- Systems theory concepts of hierarchy and recursion apply to DSE, based on the hierarchical nature of intentionality.
- Control theory is an integral theory of DSE, since goals are achieved by controlling the output states of state variables of functions within intended ranges.
  - Control of state variables can be achieved either passively through design margins, or actively through closed-loop or open-loop control systems.
- Knowledge about the parts of the system is generally constructed and maintained in disciplinary and institutional organization structures.
- The vast majority of system failures are caused by individual human cognitive or performative mistakes, or by human social lack of communication or miscommunication.
  - Mistakes due to lack of communication and miscommunication most frequently occur at institutional and disciplinary boundaries.

*Developed by UCCS/Stephen Johnson

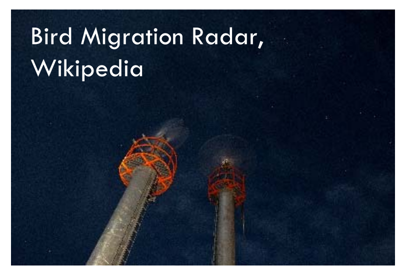
Mars Mission simplified GFT Example



- Crewed BEO Mission Goal Types
  - Transportation
  - Crew health and safety
  - Scientific and Technical

Model Selection Lessons Learned

- Biological, Ecological, Meteorological, Zoological studies have dealt with large populations/data and changes to these populations/data over many years
- This can generate very large data sets
- The statistical analysis techniques for these large data sets (big data) provide good insight into model selection for complex systems and complex adaptive systems



Model Selection Lessons Learned

- Models must have a scientific basis for their selection
- Parsimony
  - "Everything should be made as simple as possible, but no simpler" – attributed to Albert Einstein
  - Avoid over fitting the data and under fitting the data
- Avoid Over Analysis of data sets
  - A-priori model candidates defined before data set testing
  - Post-priori identification of models can lead to over emphasis of secondary or tertiary effects or the under emphasis of primary effects (or the failure to identify these)
    - "It is widely acknowledged by empirical researchers that data [dredging] is a dangerous practice to be avoided…" (White, G. C., "Population viability analysis: data requirements and essential analysis", in *Research Techniques in Animal Ecology: Controversies and Consequences*", Boitani, L., Fuller, T. K. (eds.), Columbia University Press, 2000)
    - Over fitting, spurious parameter estimates, inclusion of unimportant variables
- Model Selection Bias
  - Bias to overemphasize or underemphasize model parameters
    - Meteorological examples (Miller, A. J, Subset Selection in Regression, Chapman and Hall, London, 1990)
- Model Selection Uncertainty
  - Uncertainty in parameter and variable estimates can lead to higher confidence intervals than data actually supports
- Reference: Burnham, K. P., Anderson, D. R., Model Selection and Multimodel Inference: A Practical Information Theoretic Approach, 2nd edition, Springer, NY, 2002.

Concept of Model Complexity Supporting Decisions

- Which sub/system → What information model is important?

$$AICc(F) = -2\left(I^{KL}(F|G)\right) + 2K + \frac{2K(K+1)}{n-K-1}$$

Sensor Inputs (Information) | Information Model | Decision

Let Sensor A be continuous data (e.g. Temperature)
Let Sensor B be discrete data (e.g. Fluid Level)
Let Sensor C be binary data (e.g. Pump 'on' = 1, 'off' = 0)

Safe?

Standard Method

Need ALL sensor data and complex model to assess state of system and make decision:
Model = f(A, B, C, AB, AC, BC, ABC)

Required Sensors: A, B, C

Sensors / Location

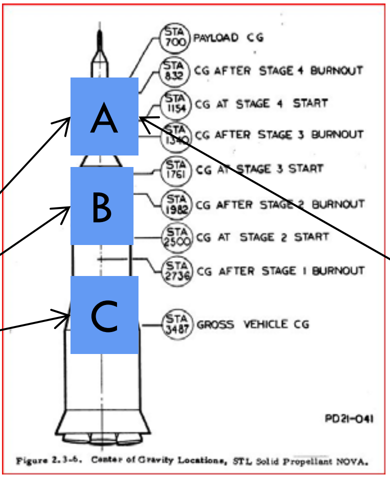


Figure 2.3-6. Center of Gravity Locations, STL Solid Propellant NOVA.

Proposed Method

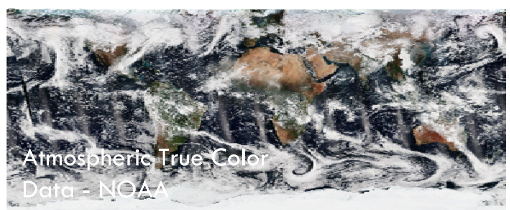
Only include relevant information to decision with same efficacy:
Model = f(A)

Required Sensor: A

Exergy-Based Information for Systems Analysis, Doty

Summary

- Natural Systems provide the best examples of Complex Systems and Complex Adaptive Systems
- Biological, Ecological, Meteorological, and Zoological studies have dealt with large populations and “big data” for decades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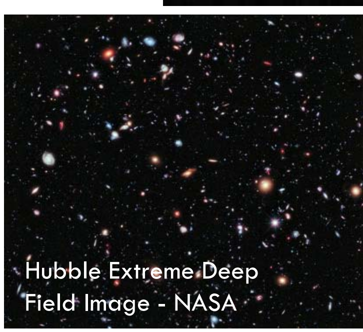
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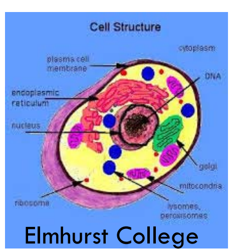

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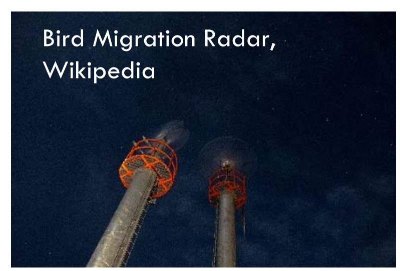
USS Enterprise, Wikipedia


Bird Migration Radar, Wikipedia


Bar-tailed Godwit Migration, Wikipedia